

Improved yield estimation technique for rice and wheat in Uttar Pradesh, Madhya Pradesh and Maharashtra States in India

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सार – फसल की कटाई के बाद की कृषि-गतिविधियों की अग्रिम योजना के लिए फसल की पैदावार का वास्तविक समय और स्थान विशेष पर सटीक आकलन आवश्यक है। मौसमी प्राचल फसल के जीवन-काल के दौरान अंतिम फसल-उत्पादन को प्रभावित करते हैं। उपज का सटीक पूर्वानुमान प्राप्त करने के लिए सुदूर संवेदन (Remote Sensing) वास्तविक वनस्पति की स्थान विशेष की जानकारी प्रदान कर सकता है। इससे पहले, फसल की उपज का आकलन करने के लिए मौसम चर (variables) जैसे - वर्षा, तापमान और सापेक्षिक आर्द्रता सहसंबंध भारित प्रतीपगमन (Regression) मॉडल में शामिल किए गए थे। इसके अलावा, उपग्रहों से किये जाने वाले रिमोट सेंसिंग से प्राप्त वी. सी. आई. (वनस्पति स्थिति सूचकांक) को भी शीतकालीन गेहूँ की पैदावार के आकलन हेतु अपनाया गया। आमतौर पर फसल के बढ़ने और पैदावार का अनुमान विभिन्न तरीकों से किया जाता है, जैसे कि मौसम चर आधारित मॉडल, रिमोट सेंसिंग आधारित मॉडल और फसल कटाई के प्रयोगों (राज्य कृषि विभाग द्वारा) के माध्यम से भी। हालाँकि इस शोध पत्र में, मौसम प्राचल और वी. सी. आई. डेटा के संयोजन से प्राप्त वास्तविक समय पर स्थान विशेष की उपज पूर्वानुमान में प्रयुक्त प्रेडिक्टर्स का उपयोग करके उपज का अधिक सटीक अनुमान लगाने का प्रयास किया गया है। उत्तर प्रदेश, मध्य प्रदेश और महाराष्ट्र के चयनित जिलों के लिए चावल (*Oryza sativa* एल.) और गेहूँ (*Triticum aestivum* एल.) के उत्पादन का पूर्वानुमान करने हेतु वर्ष 2016, 2017 और 2018 में खरीफ और रबी ऋतुओं के दौरान पिछले आंकड़ों पर आधारित सांख्यिकीय तकनीक को अपनाया गया है। इसमें ऐतिहासिक डेटा अर्थात् 2004 से 2014 तक के वास्तविक उत्पाद डेटा की मदद ली गई है। प्रस्तावित मॉडल (मौसम और रिमोट सेंसिंग के संयोजन) द्वारा दिए गए उपज पूर्वानुमान राज्य कृषि विभागों द्वारा प्रदान किए गए वास्तविक उत्पादन डेटा के साथ सत्यापित किये गए और सकारात्मक युग्मित तुलनात्मक परिणाम से पता चलता है कि इसे रबी और खरीफ दोनों ऋतुओं की फसलों के लिए स्थान विशेष के उपज की अधिक सटीकता के साथ पूर्वानुमान जारी करने हेतु व्यावहारिक रूप से लागू किया जा सकता है।

ABSTRACT. Real time and location specific accurate estimation of crop yields is essential for advance planning of post harvesting agricultural activities. Weather parameters affect final crop production during crop life span. For getting accurate yield forecast, remote sensing can provide the location specific information of actual vegetation. Previously, weather variables viz., rainfall, temperature and relative humidity were incorporated in Correlation Weighted Regression Models for estimating crop yield. Moreover, VCI (Vegetation Condition Index) retrieved from satellite remote sensing was also adopted to forecast the winter wheat yields. Usually, crop performance and yield are predicted by different methods like weather parameters based models, Remote sensing (VCI) based models and also through crop cutting experiments (by State Agriculture Departments). However, in this paper, effort has been made to estimate yield more precisely by using combination of weather parameters and VCI data to get real time location specific yield forecasting predictors. To generate Rice (*Oryza sativa* L.) and Wheat (*Triticum aestivum* L.) yield forecast for selected districts of Uttar Pradesh, Madhya Pradesh and Maharashtra, statistical technique has been adopted during *Kharif* and *Rabi* seasons in years 2015, 2016 and 2017 with the help of historical data i.e., actual production data from 2004 to 2014. Yield forecasts generated by proposed model (combination of weather and remote sensing) were validated with actual production data provided by State Agriculture Departments and positively coupled comparison results imply that it can be applied in practice for both *Rabi* and *Kharif* season crops to generate location specific yield forecast more accurately.

Key words – Remote Sensing, VCI, NDVI, HI (Harvest Index), FASAL, TCI.

1. Introduction

Crop yield forecasting is an important computational process, which is essential for agriculture along with

allied sectors and key input in national socio-economic planning. One of the ongoing approaches of crop production estimation in India involves sample surveys based on crop cutting experiments (CCE).

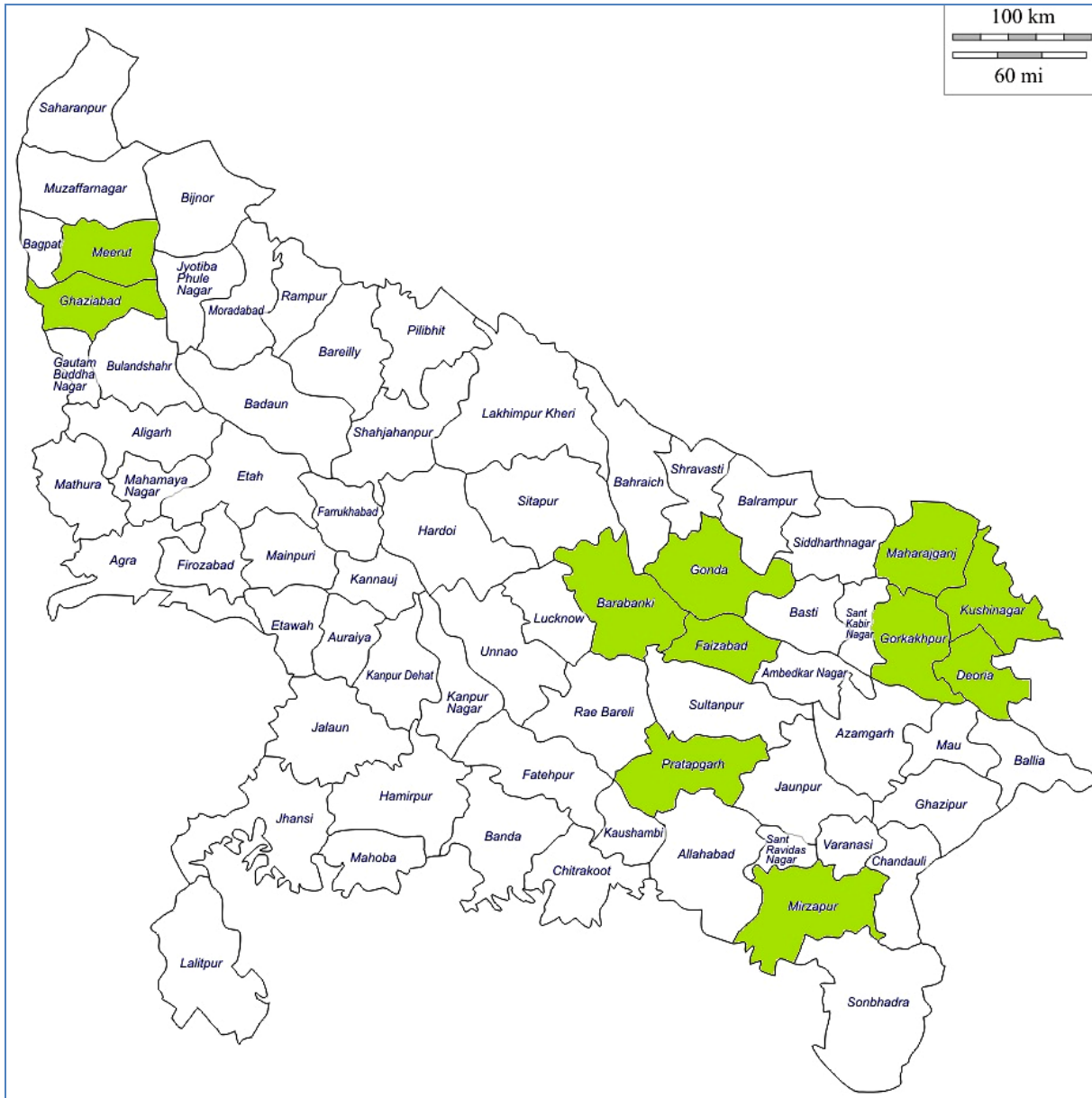


Fig. 1. Districts chosen for the crop yield study in Uttar Pradesh

These yield surveys are being performed by State agriculture departments. As plot yield data are being collected under scientifically designed complex sampling method that is based on a stratified multistage random sampling, the production estimates are available much late after end of crop season. However, the policymakers need production estimation of major crops before end of their season for decision making regarding pricing, marketing, distribution, storage, export/import etc. Hence, developing the methodology for accurate estimation of crop production in advance was the next challenge.

In line with the above scope, Ghosh *et al.* (2014) proposed an in-season yield estimation technique, which is widely popular under FASAL project. Modified Hendrick & Scholl model (Agrawal *et al.*, 1982, 1983 and 1986) using composite weather indices were used for developing the district level yield forecast models. During the process of development of the models, simple and weighted weather indices were prepared for individual weather variables as well as for interaction of two at a time considering throughout the crop-growing season. Performance of such models for major crops in various States of India suggests their limited accuracy at districts level.

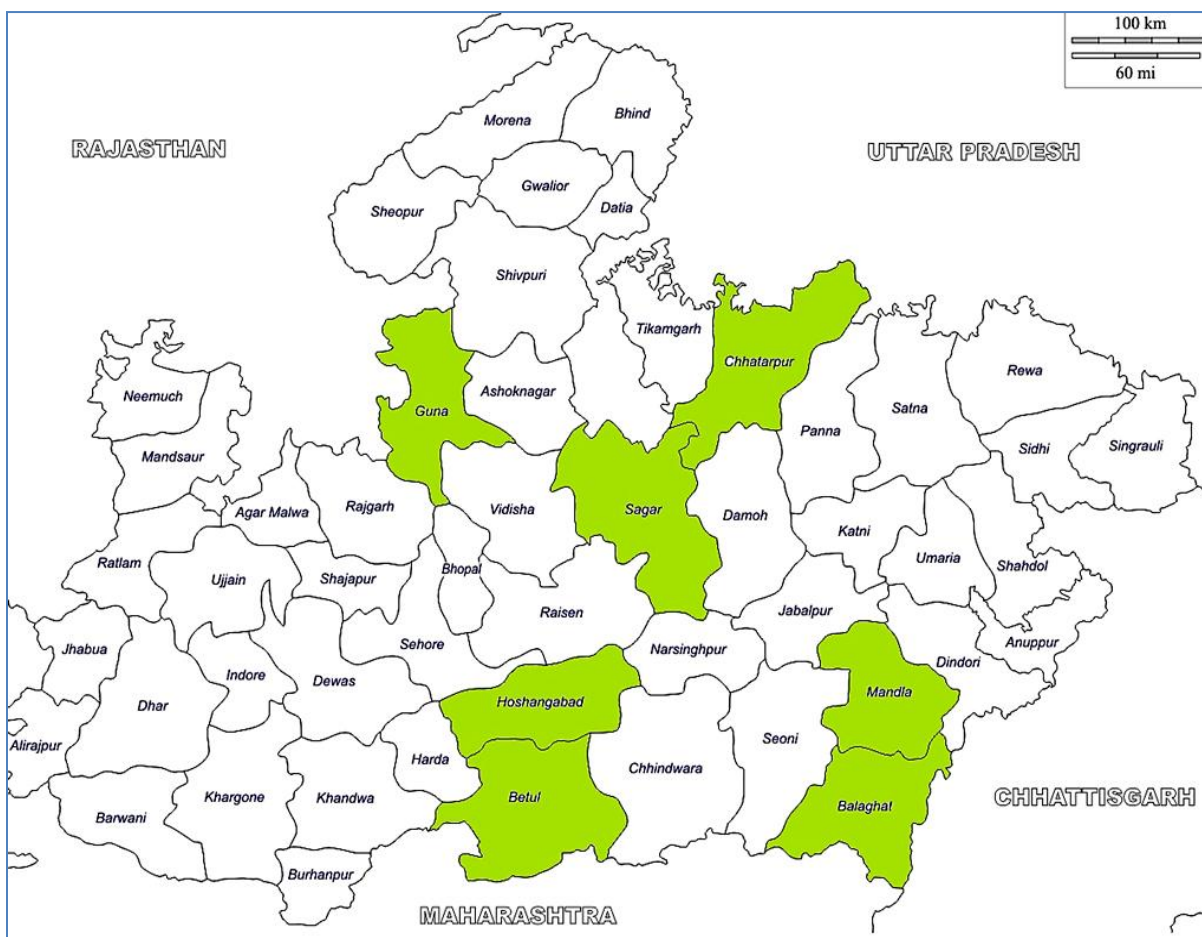


Fig. 2. Districts chosen for the study in Madhya Pradesh

Simultaneously, attempts were made for yield estimations through satellite based agro-meteorological parameters - Normalized Difference Vegetation Index (NDVI) or Vegetation Condition Index (VCI), Evapotranspiration, crop-water demand estimation, Aridity Index, Temperature Condition Index (TCI). Kogen (1997) attempted to develop global drought watch using satellite remote sensing based NDVI and VCI indices. The validation of these results concluded the utility of VCI and TCI as a sole source of information about vegetation stress due to moisture deficiency as a major cause of decline in the yield. According to Mildrexler *et al.* (2018) and Fengsong Pei *et al.* (2018), they were mainly useful for real-time assessments of vegetation condition as well as impact of weather on vegetation. This information is especially beneficial when location specific weather data is not available. Therefore, if real-time weather information is combined with the satellite-derived products then it can be used as a comprehensive tool to monitor vegetation stress, drought estimates and weather impact assessment.

Further, Prasad *et al.* (2006) and Dubey *et al.* (2018) also attempted to predict yields for several crops in Iowa State of U.S.A. and rice respectively. They concluded that NDVI derived VCI data can be used as an operational predictor for the estimation of rice crop. However, it was also found that the relation between VCI and yield is poor in some places.

Current study focuses on how to use weather parameters and remote sensing together to overcome the shortcomings in existing yield prediction models such as unavailability of weather data, poor resolution of weather observing network, lack of present physical condition of crops, sampling errors etc. Moreover, adding remote sensing to existing weather based statistical models will incorporate a location specific real-time physical condition inputs to the models. Weather based model may not capture the yield prediction well if crop was damaged due to hazardous weather, e.g., drought, hailstorm, frost etc. However, the same would be reflecting very well in vegetation condition indices derived from satellite remote

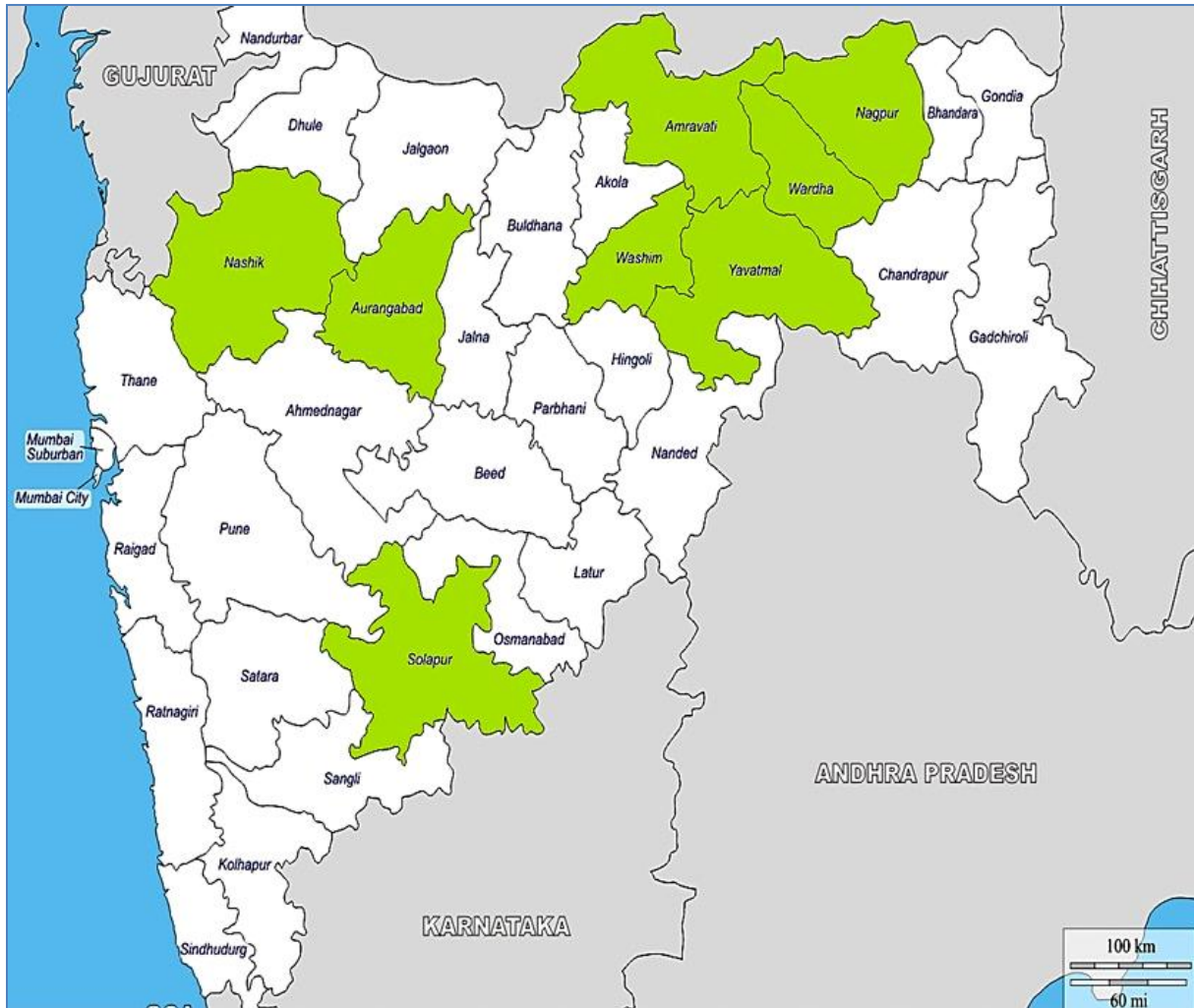


Fig. 3. Districts chosen for the study in Maharashtra

sensing data as stated by Liu and Kogan (1996) and would be helpful in accurate yield prediction.

2. Area of study

Soft wheat (*Triticum aestivum* L.) and rice (*Oryza sativa* L.) are the main food grains in Indian subcontinent by people at large, especially in Gangetic plains and peninsular India. Twenty six districts in which wheat and rice are majorly grown in the past decade in the three States of Uttar Pradesh, Madhya Pradesh and Maharashtra in India were considered for this study. The State wise distribution of selected districts is given below:

(i) Uttar Pradesh: Total 11 districts were selected from U.P. State - Gorakhpur, Deoria, Kushinagar, Maharajganj, Gonda, Ghaziabad, Meerut, Mirzapur, Pratapgarh, Barabanki and Faizabad (area is shown in Fig. 1).

(ii) Madhya Pradesh: Total 7 districts were selected from M. P. State - Betul, Hoshangabad, Guna, Sagar, Chhatarpur, Balaghat and Mandala (area is shown in Fig. 2).

(iii) Maharashtra: Total 8 districts were selected from Maharashtra State - Nashik, Aurangabad, Solapur, Washim, Yavatmal, Amravati, Wardha and Nagpur (area is shown in Fig. 3).

3. Data / material

Daily Data on weather parameters were collected from National Data Center (NDC), IMD, Pune for the period 1971-2017. Fortnightly values of Vegetation Condition Index (VCI) were collected from Mahalanobis National Crop Forecast Center (MNCFC), New Delhi for the period 2004-2017 with 2 km × 2 km and 8 km × 8 km resolutions. Crop Production Statistics of Rice and Wheat for the period 1990-2017 were collected from Directorate

of Economics and Statistics, Department of Agriculture, Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare (websites) and State Agriculture Departments. Analysis was performed using the IBM SPSS software.

Remote sensing indices: Vegetation Condition Index (VCI) was used to determine temperature-related vegetation stress as well as stress caused by an excessive wetness. Further, normalized difference vegetation index (NDVI) is used to compute vegetation condition index (VCI) and provides statistical information regarding actual crop condition.

4. Methodology

Meteorological parameters at various crop growth stages along with detrended yield are used in the empirical models. It is assumed that yield is increasing every year due to continuous improvement in technology; hence, yield is de-trended by removing technological trends.

To prepare weather based empirical crop yield forecasting model, Long term (30 years or more) time-series meteorological data of major weather parameters (T_{max} , T_{min} , RH-I, RH-II and BSS/ Rainfall) is required. However, fortnightly VCI data for crop growing season is used to prepare VCI based empirical crop yield forecasting model.

Methodology of proposed model includes two major steps, first is to develop multiple linear regression model with existing weather parameters and second is to incorporate the VCI parameters and corresponding weights in the model. Both the steps are described herein.

4.1. Multiple Linear Regression Model

Models suggested by Fisher (1924) and Hendrick and Scholl (1943) used small number of estimated parameters for taking care of distribution pattern of weather over the crop season as follows:

$$Y = A_0 + a_0 \sum_{w=1}^n X_w + a_1 \sum_{w=1}^n w^1 X_w + a_2 \sum_{w=1}^n w^2 X_w + e$$

where, Y is model output (Forecasted yield); X_w denotes value of combination of weather variables under study in w^{th} week ($w = 1, 2, \dots$); n is the number of weather variables; and A_0 , a_0 , a_1 and a_2 are the model parameters.

This model was extended to study combined effects of weather variables and an additional variate T representing the year for time trend as follows:

$$Y = A_0 + \sum_{i=1}^p \sum_{j=0}^1 a_{ij} Z_{ij} + \sum_{i \neq i'=1}^p \sum_{j=0}^1 a_{ii'j} Z_{ii'j} + cT + e$$

where,

$$Z_{ij} = \sum_{w=1}^m r_{iw}^j X_{iw}$$

and

$$Z_{ii'j} = \sum_{w=1}^m r_{ii'w}^j X_{iw} X_{i'w}$$

Here, r_{iw} is correlation coefficient of yield with i^{th} weather variable (x) in w^{th} week period; $r_{ii'w}$ is correlation coefficient of yield with product of i^{th} and i'^{th} weather variables (x) in w^{th} week period; m is period of forecast; p is number of weather variables used, e is random error distributed as $N(0, \sigma^2)$ and T is time factor (technology-trend). This customization includes effects of quadratic terms of weather as well as effects as linear function of respective correlation coefficients.

4.2. Inclusion of VCI variables

The various weather variables used in the weather based models (described in section 4.1) are given in following Table 1 and denoted by symbols Z_{10} to Z_{451} . In current study, yield forecasts were firstly generated by regression model using weather parameters mentioned herewith. However, VCI variables (denoted by symbols Z_{560} and Z_{561} in Table 1) were further introduced in regression model to develop combination model (considering weather and VCI inputs together) and then to set weights by correlation analysis between actual yield and VCI data series.

4.3. VCI

Kogan (1995) proposed a vegetation condition index based on the relative NDVI change with respect to maximum and minimum historical NDVI value. It is defined as follows:

$$VCI = \frac{NDVI_{x,y} - NDVI_{min\ x,y}}{NDVI_{max\ x,y} - NDVI_{min\ x,y}} \times 100\%$$

where,

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

TABLE 1

Weather variables and their combination variables used in statistical model along with VCI variables used in proposed model

Symbols	Description	Symbols	Description
Z ₁₀	Unweighted coefficients for BSS	Z ₁₁	Weighted coefficients for BSS
Z ₂₀	Unweighted coefficients for T _{max}	Z ₂₁	Weighted coefficients for T _{max}
Z ₃₀	Unweighted coefficients for T _{min}	Z ₃₁	Weighted coefficients for T _{min}
Z ₄₀	Unweighted coefficients for morning hours humidity	Z ₄₁	Weighted coefficients for morning hours humidity
Z ₅₀	Unweighted coefficients for evening hours humidity	Z ₅₁	Weighted coefficients for evening hours humidity
Z ₁₂₀	Unweighted coefficients for BSS * T _{max}	Z ₁₂₁	Weighted coefficients for BSS * T _{max}
Z ₁₃₀	Unweighted coefficients for BSS * T _{min}	Z ₁₃₁	Weighted coefficients for BSS * T _{min}
Z ₁₄₀	Unweighted coefficients for BSS * Morning hours humidity	Z ₁₄₁	Weighted coefficients for BSS * Morning hours humidity
Z ₁₅₀	Unweighted coefficients for BSS * Evening hours Humidity	Z ₁₅₁	Weighted coefficients for BSS * Evening hours Humidity
Z ₂₃₀	Unweighted coefficients for T _{max} * T _{min}	Z ₂₃₁	Weighted coefficients for T _{max} * T _{min}
Z ₂₄₀	Unweighted coefficients for T _{max} * Morning hours humidity	Z ₂₄₁	Weighted coefficients for T _{max} * Morning hours humidity
Z ₂₅₀	Unweighted coefficients for T _{max} * Evening hours Humidity	Z ₂₅₁	Weighted coefficients for T _{max} * Evening hours Humidity
Z ₃₄₀	Unweighted coefficients for T _{min} * Morning hours Humidity	Z ₃₄₁	Weighted coefficients for T _{min} * Morning hours Humidity
Z ₃₅₀	Unweighted coefficients for T _{min} * Evening hours Humidity	Z ₃₅₁	Weighted coefficients for T _{min} * Evening hours Humidity
Z ₄₅₀	Unweighted coefficients for Morning hours Humidity * Evening hours Humidity	Z ₄₅₁	Weighted coefficients for Morning hours Humidity * Evening hours Humidity
Z ₅₆₀	Unweighted coefficient for Vegetative Climate Index	Z ₅₆₁	Weighted coefficient for Vegetative Climate Index

$NDVI_{min}$ = Historical NDVI time series minimum,

$NDVI_{max}$ = Historical NDVI time series maximum,

x and y are Geo-location coordinates of the time series NDVI at location,

(x, y) across entire time span of the time series NDVI at location.

This normalized index indicates percent change of the difference between the current NDVI index and historical NDVI time series minimum with respect to the NDVI dynamic range, *i.e.*, +1 to -1. It focuses on the impact of drought on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values, ultimately a truth indicator of present vegetation condition of the crop. Further, Nir Krakauer

et al. (2017) stated that, these values are needed to be corrected by doing ground trothing, *i.e.*, information provided by direct observation.

4.4. R-square value

It is a statistical measure of how close the data are to the fitted regression line. It is the percentage of the response variable variation that is explained by a linear model.

$$R\text{-squared} = \text{Explained variation} / \text{Total variation}$$

R-square value is always between 0 and 100% (or 1.0 in fraction form) while 0% indicates that the model explains none of the variability of the response data around its mean, while 100% indicates that the model explains all the variability of the response data around its mean.

TABLE 2

Weather based model - Yield forecast for rice in the districts of leading production in U. P., M. P. and Maharashtra for year 2016

District	Final model equation	Weather parameters	Forecast yield (kg/ha)	R ²	F	Standard error
Ghaziabad	$Y = 1206.58 + 0.56*Z_{141}$	Tmax*RH-I	2388	0.72	10.4	101.1
Gonda	$Y = 2128.39 + 90.21*Time + 0.91*Z_{121}$	Tmax*Tmin	2714	0.97	84.7	62.4
Gorakhpur	$Y = 1094.39 - 8.16*Z_{31} + 62.90*Time + 0.89*Z_{151} + 0.37*Z_{231}$	RF, Tmin*RF, Tmax*RH-II	2231	0.99	184.9	28.9
Balaghat	$Y = 3340.46 + 0.02*Z_{131} + 0.32*Z_{141}$	Tmax*RF, Tmax*RH-I	2298	0.89	30.6	37.1
Nagpur	$Y = 277.92 + 44.14*Z_{21} + 0.01*Z_{341}$	Tmin, RF*RH-I	2173	0.98	84.0	27.1
Nashik	$Y = -327.79 + 123.14*Time + 0.13*Z_{451}$	RH-I*RH-II	2846	0.91	36.8	141.9

TABLE 3

Remote sensing (VCI) based model - Yield forecast for rice in the districts of leading production in U. P., M. P. and Maharashtra for year 2016

District	Final model equation	VCI parameters	Forecast yield (kg/ha)	R ²	F	Standard error
Ghaziabad	$Y = 2759.8 - 6.07*July\ 2^{nd}\ VCI$	VCI of 2 nd fortnight of July month	2356	0.71	10.0	102.3
Gonda	$Y = 1577.61 + 92.97*Time$	-	2693	0.76	22.1	153.1
Gorakhpur	$Y = 1594.40 + 62.45*Time$	-	2406	0.52	8.6	193.2
Balaghat	$Y = 2528.43 - 5.01*July\ 1^{st}\ VCI$	VCI of 1 st fortnight of July month	2271	0.54	9.3	73.7
Nagpur	No variable	-	-	-	-	-
Nashik	$Y = 1189.73 + 118.36*Time$	-	2728	0.73	19.7	242.2

4.5. *F*-statistic

This value, we get when we run an ANOVA test or a regression analysis to find out whether the means between two populations are significantly different. It is most often used when comparing statistical models that have been fitted to a data set, in order to identify the model that best fits the population from which the data were sampled.

4.6. *Standard error*

This statistical term measures the accuracy with which a sample represents a population. For the proposed model,

Error percentage

$$= \left[\frac{\text{Forecasted yield} - \text{Actual crop yield}}{\text{Actual crop yield}} \right] \times 100$$

5. Results and discussion

Weather based model, Remote sensing based model and combination model (considering weather and VCI variables together) were run to generate yield forecasts of rice and wheat for selected districts of U. P., M. P. and Maharashtra for the years 2015, 2016 and 2017. Model-wise statistical validation of yield forecasts generated with actual production data is discussed herein.

5.1. *Analysis of all three models for rice yield forecast*

In the results shown here, various variables applicable finally in the model, computation of their output errors and comparison of all three methods (weather based model, VCI based model and combination of weather & VCI together) were done for rice (*Kharif*) crop for selected areas of U. P., M. P. and Maharashtra.

TABLE 4
Combination model (Weather and VCI together) - Yield forecast for rice in the districts of leading production in U. P., M. P. and Maharashtra for year 2016

District	Final model equation	Weather and VCI parameters	Forecast yield (kg/ha)	R ²	F	Standard Error
Ghaziabad	$Y = 1804.34 + 4.18*Z_{61} + 0.04*Z_{160}$	VCI, Tmax*VCI	2429	0.99	158.9	21.4
Gonda	$Y = 2128.39 + 90.21*Time + 0.91*Z_{121}$	Tmax*Tmin	2714	0.97	84.7	52.4
Gorakhpur	$Y = 1566.09 - 10.45*Z_{31} + 60.71*Time + 0.63*Z_{151} + 0.47*Z_{230} - 0.01*Z_{460}$	RF, Tmax*RH-II, Tmin*RF, RH-I*VCI	2115	0.99	815.4	12.3
Balaghat	$Y = 3559.62 + 0.02*Z_{131} + 0.30*Z_{141} - 0.01*Z_{160}$	Tmax*RF, Tmax*RH-I, Tmax*VCI	2228	0.95	41.6	26.8
Nagpur	$Y = 2582.73 + 0.01*Z_{361} + 0.15*Z_{251} + 0.10*Z_{121} - 0.03*Z_{120} + 0.0001*Z_{351} + 0.002*Z_{240}$	RF*VCI, Tmin*RH-II, Tmax*Tmin, RF*RH-II, Tmin*RH-I	2344	1.00	83.7	0.03
Nashik	$Y = 1163.21 + 131.06*Time + 0.04*Z_{361}$	RF*VCI	2718	0.91	37.3	41.2

TABLE 5
Comparison of Weather based and Remote Sensing (VCI) based models with proposed combination model (of weather and remote sensing) for wheat crop yield forecast in the districts of leading production in U. P., M. P. and Maharashtra for year 2016

District	Weather based model					VCI based model					Weather + VCI based model (in the current literature)				
	Forecasted yield (kg/ha)	R ²	F	Std. error	Error (%)	Forecasted yield (kg/ha)	R ²	F	Std. error	Error (%)	Forecasted yield (kg/ha)	R ²	F	Std. error	Error (%)
Washim	2930	0.72	11.4	91.1	16.01	2876	0.81	10	102.1	15.23	2790	0.99	148.9	19.4	14.61
Sagar	3120	0.91	75.7	72.4	0.92	2900	0.66	19.1	129.2	1.34	2821	0.97	94.7	52.4	0.62
Gorakhpur	2321	0.93	165.9	38.9	10.1	2400	0.62	5.6	152.9	-2.1	2410	0.99	725.4	11.3	-3.2
Guna	2498	0.81	29.7	27.1	0.69	2567	0.62	8.1	79.2	3.57	2345	0.95	51.6	16.8	3.6
Meerut	2278	0.97	81	47.1	16.1	2341	0.71	10.1	61.9	16.9	2290	0.99	93.7	1.03	2.51
Aurangabad	3465	0.93	31.8	131.7	-9.1	3200	0.73	21.7	200.9	-9.6	3216	0.91	47.3	31.2	-3.4

In Table 2, rice crop yield forecast for year 2016 generated by weather based model, are shown. Here, it is clearly inferred that R² value is above 0.7 but standard error percentage is varying between low values (28.9) to high values (141.9). Hence, satisfactory confidence level could not be achieved here while performing district-wise rice yield prediction.

In Table 3, rice crop yield forecast for year 2016 generated by VCI based model, are shown. Here also, it may be clearly inferred that R² value is above 0.5 along with high values of standard error (73 and above). Hence, accuracy could not be achieved using VCI parameter alone.

In Table 4, rice crop yield forecast for year 2016 generated by combination (of weather and VCI together) model, are shown. Interestingly, it may be clearly inferred that R² value is above 0.95 along with low values of standard error (52 and below). Hence, accuracy could be achieved using both weather parameters and fortnightly VCI data. In addition, confidence level of model output was found to above 95%.

5.2. Comparison of all three models for wheat yield forecast

In the Table 5 shown here, output error computation and comparison of all three methods (weather based

model, remote sensing (VCI) based and combination model (weather and VCI together) were done for wheat (*Rabi*) crop for selected districts of U. P., M. P. and Maharashtra for year 2016.

In year 2015 and 2016, the leading production districts of wheat crop were Sagar, Gorakhpur, Meerut, Guna, Aurangabad and Washim among the selected districts of U. P., M. P. and Maharashtra. Similar to Tables 3&4; Table 5 summarizes the results for wheat crop, *i.e.*, comparison of model forecast altogether with mentioning R^2 , F and percentage error values for wheat crop.

From the above tables, following results may be drawn:

(i) Neither weather based model nor Remote sensing (VCI) based model could achieve confidence level 95% or higher universally (comparing R^2 stats for both the models) while combination model gains at least 95% confidence level for all districts.

(ii) The range of F-stat for existing models is higher with least value is 10, however its least value is 37.3 for combination model. It means that combination model with higher values of F-stat provides better fitment to yield data.

(iii) For all districts, combination model percentage error is either less than those for existing models or less negative (in case of Aurangabad). It means that accuracy of proposed combined model is better than mere weather based or VCI based model. Moreover, it is capable to provide yield forecast nearer to real yield for the rice and wheat crops.

6. Conclusions

Rice yield forecasting was being done independently by weather based model approach using weather parameters and remote sensing models approach using VCI. Accuracy of any such existing models cannot be increased after certain extent. For the first time, we tested the usability of the models together and proposed a combination model (of weather and Remote Sensing); found that it could provide best results among the three. The utilization of remote sensing data (VCI) with various spatial and temporal resolutions is able to settle the problem of lacks of crop physical condition in existing model. This study can be helpful to forecast crop yield more accurately and new combination model approach has all the strength for operationalizing yield forecasting in different crops.

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References

- Agrawal, Ranjana and Jain, R. C., 1982, "Composite model for forecasting rice yield", *Ind. J. Agri. Sci.*, **52**, 3, 189-194.
- Agrawal, Ranjana, Jain, R. C. and Jha, M. P., 1983, "Joint effects of weather variables on rice yields", *Mausam*, **34**, 2, 177-181.
- Agrawal, Ranjana, Jain, R. C. and Jha, M. P., 1986, "Models for studying rice crop-weather relationship", *Mausam*, **37**, 1, 67-70.
- Dubey, S. K., Gavli, A. S., Diwakarand, K. and Ray, S. S., 2018, "Use of vegetation condition index for rice yield forecasting", *Indian Society of Remote Sensing (PHOTONIRVACHAK-J IND)*, 2018.
- Fengsong, Pei, Changjiang, Wu, Xiaoping, Liu, Xia, Li, Kuiqi, Yang, Yi, Zhou, Kun, Wang, Li, Xu and Gengrui, Xia, 2018, "Monitoring the vegetation activity in China using vegetation health indices", *Agricultural and Forest Meteorology*, **248**, 215-227.
- Fisher, R. A., 1924, "The influence of rainfall on the yield of wheat at Rothamsted", *Roy. Soc. (London), Phil. Trans. Ser. B.*, **213**, 89-142.
- Ghosh, K., Balasubramanian, R., Bandopadhyay, S., Chattopadhyay, N., Singh, K. K. and Rathore, L. S., 2014, "Development of crop yield forecast models under FASAL - A case study of *kharif* rice in West Bengal", *Journal of Agrometeorology*, **16**, 1, 1-8 (June, 2014).
- Hendrick, W. A. and Scholl, J. C., 1943, "Technique in measuring joint relationship. "The joint effects of temperature and precipitation on crop yield", *N. Carolina Agric. Exp. Stat. Tech. Bull.*, p74.
- Kogan, F. N., 1995, "Application of vegetation index and brightness temperature for drought detection", *Advances in Space Research*, **15**, 11, 91-100.
- Kogan, F. N., 1997, "Global Drought Watch from Space", *Bulletin of the American Meteorological Society*, **78**, 4, 621-636.
- Krakauer, Nir, Lakhankar, Tarendra and Anadón, José, 2017, "Mapping and Attributing Normalized Difference Vegetation Index Trends for Nepal", *Remote Sensing*, **9**, 10, 986, doi:10.20944/preprints201709.0032.v1.
- Liu, W. T. and Kogan, F. N., 1996, "Monitoring regional drought using the Vegetation Condition Index", *International Journal of Remote Sensing*, **17**, 14, 2761-2782.

Mildrexler, D. J., Zhao, M., Cohen, W. B., Running, S. W., Song, X. P. and Jones, M. O., 2018, "Thermal anomalies detect critical global land surface changes", *Journal of Applied Meteorology and Climatology*, **57**, 2, 391-411.

Prasad, K. Anup, Chai, Lim, Singh, Ramesh P. and Kafatos, Menas, 2006, "Crop yield estimation model for Iowa using remote sensing and surface parameters", *International Journal of Applied Earth Observation and Geoinformation*, **8**, 26-33.
